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FULL ARTICLE

Highlighting action and environmental component interactions using a Network Theory approach

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ABSTRACT

In Environmental Impact Assessment (EIA), the either positive or negative impacts that specific N project actions might generate on a number M of environmental components are typically summarized in the form of Interaction Matrix (IM). This is a $N \times M$ tabular array containing numbers whose sign and magnitude represent the type and severity of impacts. Current approaches to interpret the IM mainly remain on a qualitative level which are limiting its practical usage. In this work, we build on previous works and adopt network theory as a methodology to represent the IM in a graphical form, and to obtain quantitative information that can be inserted in the EIA. The IM corresponds to a bipartite network linking actions and environmental components. The associated network is useful to perform quantitative statistical analyses, which summarise the complexity of cross and mutual interconnections between actions and environmental components under simple and understandable metrics. We show some results from EIAs related to water projects and other case studies, whose different complexity helps to appreciate the general applicability of the method.

KEYWORDS

Environmental Impact Assessment (EIA); Network theory; Bipartite networks; Impact evaluation

1. Introduction

In the year 1969 Environmental Impact Assessment (EIA) has been established with the National Environmental Policy Act (Marriott 1997) by the U.S. for the very first time. Since and by the 1990s EIA had become an integral part of civil and environmental engineering projects, for example, water resources projects promoting storage reservoirs, extensive ground water pumping, etc. (Jain and Singh 2003; Morris and Therivel 2009). The purpose of the EIA is therefore to identify the positive and negative impacts that will be caused by a specific project on both the short and the long term and to describe them qualitatively in the form of a technical report. Eventually, results from the EIA are assembled in successive phases and used to produce the Environmental Impact Statement. State of the art is that the results of the conducted studies are compiled in tabular form as part of the technical report. At first glance the qualitative description of the results in the technical report can be very

This makes them hard to interpret, although they provide useful indications that are used to propose ameliorating solutions.

Another ~~and more quantitative~~ form to present the results of the EIA technical report is a matrix which is called the interaction matrix (Jain and Singh 2003; ICOLD 1982; Morris and Therivel 2009; Glasson et al. 2005). In the interaction matrix each impact resulting from the interactions among actions and environmental components is expressed as a number, which occupies an element of the matrix. These are the result of expert evaluations which translate qualitative results into numbers, which represent (potential) interactions and can thus be considered as primary tools to identify impacts. Beneficial impacts are symbolised by a positive sign and harmful impacts by a negative sign. The severity, either positive or negative, is typified by the value magnitude.

~~However, EIA is oftenly~~ EIA has often been criticised for being non-transparent and providing insufficient information to the public (Ijäs et al. 2010; Morgan 2012; Martínez et al. 2018). ~~Additionally, problems in the EIA practice are in particular related to impact evaluation and determination of significance.~~ In order to make EIA more understandable by improving impact evaluation and determination of its significance Addressing these problems several approaches (e.g., Ijäs et al. (2010); Mustow et al. (2005); Cloquell-Ballester et al. (2007); Perdicoulis and Glasson (2006); Barrow (1997)) have been developed to make EIA more understandable. Among those, Perdicoulis and Glasson (2006) proposed a methodology to treat the interaction matrix qualitatively for which they made. For example made use of network theory to render the interaction matrix as a network and properly identify impact. Despite stopping their analysis at a qualitative level, this approach aimed at increasing the communication with practitioners and stakeholders. , they rendered the interaction matrix as a network to describe the causal relationships in it, but they stopped their analysis at a qualitative level.

Broadly speaking, a network is a collection of points (vertices) joined together pairwise by lines (edges) (Newman 2010; Boccaletti et al. 2006). Networks allow to investigate a large number of ecological (Dormann et al. 2009; Dormann and Strauss 2014; Huxham et al. 1996; Martinez 1991) and social processes (Newman 2001a,b; Newman et al. 2001; Robins and Alexander 2004; Davis et al. 2003; Watts and Strogatz 1998; Amaral et al. 2000; Boccaletti et al. 2006) in which from the field of sociology the vast majority of mathematical and statistical tools are derived.

The impact evaluation on the basis of the interaction matrix is not a straightforward task. Particularly, impact evaluation can be very difficult because of the multiple interconnections and coupling among actions and environmental components. Martínez et al. (2018) are accounting for these multiple interconnections and developed complex network approach to determine the environmental impact in a more objective way than qualitative methodologies (e.g. Conesa (2010)). Yet, the overall potential of network theory is not fully exploited. Thus, we see the need to go beyond the current status of such works by incorporating more quantitative statistics of the classical network theory approach. The main objective of this paper is to further contribute to the disentanglement of the inherent complexity of EIA and to facilitate the statement of the EIA. For this we combine a visual representation of the bipartite network with more quantitative statistics of the classical network theory approach.

In section 2 we show that the interaction matrix can be represented as a bipartite network (Perdicoulis and Glasson 2006). In order to describe the network structure more quantitatively we propose in section 3 some measures and metrics which are of common use in network theory. We mention briefly which measure we make use of

to delineate the structural features of the network. Then, in order to exemplify our approach section 4 shows the results of the application to three actual case studies available in the literature. We provide the software for the visualisation and analysis of the interaction matrix in the form of the R-package *BiNetEIA* (<https://github.com/schwemro/BiNetEIA>; R Core Team (2017)) as supplementary material, which also encompasses the data of the case studies. The software and the data are freely available.

2. Theory

2.1. Interaction matrix as a bipartite network and related 1-mode projections

The interaction matrix corresponds to a bipartite network (or simply two-mode), whose characteristic feature is that edges only link vertices of unlike type (Newman 2010; Boccaletti et al. 2006). Consequently, the edges connect actions and environmental components. The general network building process is outlined in Fig. 1. However, as we will make use of three real case studies, which supply the relevant interaction matrices, we skip the first step in which the interaction matrix is derived from the technical report and assume it to be known. The interaction matrix is a rectangular matrix, where n is the number of actions and m is the number of environmental components. In the network theory jargon of bipartite networks this is known as *incidence matrix* whose elements B_{ij} can be expressed as

$$B_{ij} = \begin{cases} w & \text{if environmental component, } j, \text{ is impacted by action, } i; \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

where w symbolises the magnitude and sign of an impact. These can be either positive or negative. In order to treat the incidence matrix with both positive and negative interactions we recommend to split the matrix into two matrices. The one, which contains exclusively positive interactions, and the other, which contains exclusively negative interactions. For the latter the negative signs are then changed to positive ones whilst remembering that they refer to negative effects. Should the two cases not be separated, a miscalculation of some network measures would arise such, for example, the weighted degree centrality defined later. A value of 0 can either mean that no edges exist or that the interactions are balanced.

Figure 1.: Building a bipartite network from a technical report EIA and the related interaction matrix

Figure 2.: Separation of the bipartite network into two bipartite networks with exclusively positive (green) and negative (red) interactions and their corresponding one-mode projections. The dotted line in the bipartite network exemplifies a 4-path and the dashed line in the one-mode a 3-path.

We introduce now the projected network, which is also known as the one-mode projection (or simply one-mode). This is another form of representation of the bipartite network which allows analysing the relationship of like vertices. We construct it for the actions by merely building the n -vertex network and likewise for the environmental components by forming the m -vertex network (Fig. 2) (Newman 2010). Generally, in the projection two vertices are connected, if they have at least one unlike vertex in the bipartite network in common. Applying it to the EIA means that two environmental components are linked if they are both affected by the same action; similarly, two actions are connected if they impact the same environmental component. Note, that when an environmental component or action appears disconnected it does not mean that there is no interaction. In fact, there can be a single edge or no edge at all in the two-mode. So, any intervention on an action with a single edge and also with no shared environmental components can be considered as decoupled from the others. When finally transforming the bipartite network into the related one-mode projections the corresponding weights from the bipartite network are preserved by summing them up (Padron et al. 2011). The one-mode projection leads thus to the concomitant definition of the *adjacent matrix*, which is formulated as

$$A_{ij} = \begin{cases} w & \text{if there is an edge from vertex } j \text{ to vertex } i, \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

where i and j refer now to specific actions or to specific environmental components depending on which projection is performed. In contrast to the coefficients of the bipartite network (1) the weight w of the one-mode projection is assembled from the weights of multiple edges. Multiple edges arise for example when two actions share two or more environmental components.

It is worth to notice that the one-mode projection represents "parental" relationships of either the actions or the environmental components by establishing a both graphical and quantitative link among those environmental components sharing one or more common actions and viceversa. This representation is particularly useful for highly complex networks for which singling out such relationships from the bipartite representation would be rather cumbersome (e.g., see examples in Section 3).

The network layout of the projections can be obtained by using, for example, the Fruchterman-Reingold algorithm (Luke 2015; Kolaczyk and Csárdi 2014; Fruchterman and Reingold 1991). This algorithm, listed among the class of force-directed algorithms, is mainly chosen for its aesthetical purpose (Luke 2015; Kolaczyk and Csárdi 2014). Therein, the vertices in the one-mode network can be thought as connected together by multiple springs in which the weight of an edge symbolises a spring constant. The vertices are spatially displaced such that the energy in the network is minimised. For more details on how the algorithm is working, we refer to Fruchterman and Reingold (1991).

2.2. Measures and metrics

2.2.0.1. Degree centrality, mean degree centrality and degree distribution.

The degree centrality quantifies the importance of a vertex by counting the weight of edges which are connected to a vertex (Newman 2010). Besides there exist several alternatives (for example one could also use the closeness centrality as centrality measure), but as they are strongly correlated this would end up in the same interpretation (Opsahl et al. 2010). We derive it for the bipartite network

$$k2_j = \sum_{i=1}^m B_{ij}, \quad (3)$$

$$k2_i = \sum_{j=1}^n B_{ij}, \quad (4)$$

where j identifies the environmental component, and i the action. Similarly, for the one-mode projections one defines

$$k1_j = \sum_{i=1}^m A_{ij} \quad (5)$$

$$k1_i = \sum_{j=1}^n A_{ij}, \quad (6)$$

in which case i and j identify the element of the adjacent matrix for the one-model projection of the actions in Eq.(5), and that of the environmental component in Eq.(6).

The mean degree measures arithmetically the average amount of vertices or edges a vertex is connected to (Opsahl et al. 2010). For the bipartite network we formulate

$$\overline{k2_j} = \frac{1}{n} \sum_{j=1}^n k2_j \quad (7)$$

$$\overline{k2_i} = \frac{1}{m} \sum_{j=1}^m k2_i \quad (8)$$

and for the one-mode projections

$$\overline{k1_j} = \frac{1}{n} \sum_{j=1}^n k1_j \quad (9)$$

$$\overline{k1_i} = \frac{1}{m} \sum_{j=1}^m k1_i \quad (10)$$

For further statistical characterisation of the degree centrality resulting from equations (3) and (4) one can plot its distribution in form of histograms with relative frequencies for the actions and for the environmental components and compute the related statistical moments.

2.2.0.2. Network asymmetry. For the bipartite network, this measure describes the ratio between the difference of the number of actions and the number of environmental components and the sum of them (Dormann et al. 2009). Positive asymmetry occurs if the number of environmental components are outweighing the number of actions and vice versa. Zero means the network is symmetric.

$$S = \frac{\text{no. of vertices of actions} - \text{no. of vertices of env. comp.}}{\text{no. of vertices of actions} + \text{no. of vertices of env. comp.}} \quad (11)$$

As far as the EIA is concerned, positive asymmetry indicates that the actions influence only a smaller number of environmental components, thus suggesting a lower impact of the project as far as the number of environmental actors are concerned. On the contrary, a negative asymmetry would indicate that perturbations induced by few actions spread largely on environmental components thus requiring particular care in evaluating mitigation measures.

2.2.0.3. Connectance. Defines the normalised number of connections that are realized in the bipartite network (Dormann et al. 2009), and it is obtained by dividing the number of realised edges to all theoretically possible edges. This measure is 1 if all possible connections are performed and 0 if no connections at all are existent.

$$CO = \frac{\text{No. of edges}}{n \cdot m} \quad (12)$$

2.2.0.4. Mean distance. The length of the shortest "path" in a network is called shortest "distance" reflecting the shortest way between two vertices i and j (New-

man 2010). By averaging all the shortest distances in a network we obtain the mean distance. One needs to be careful here as the concept of the distance we are using should not be confused with the geodesic distance which bases solely on the weight of the edges. We hold on Opsahl et al. (2010) in which they divided the edge weights through the average weight in the network before calculating the measure proposed by Dijkstra (1959). In this way the mean distance is normalised and reflects the average distance with average edge weight vertices are away from each other (Opsahl et al. 2010). It allows then a comparison across networks with different ranges of edge weights (Opsahl et al. 2010). Here the lower the distance is the stronger is the connection. This measure cannot be calculated for the binary network (Opsahl et al. 2010).

2.2.0.5. Clustering coefficient. Clustering addresses the cohesive tendency of vertices. A number of measures has been developed to measure this tendency (Newman 2010). However, one- and two-mode networks need to be distinguished when this measure is studied. The projected one-mode networks often include many more 3-paths (see Fig. 2) than regular one-modes and thus, the cluster coefficient will be overestimated (Opsahl 2013). We therefore investigate the clustering only in the two-mode and refer to Opsahl (2013) who redefined the coefficient for two-mode networks for calculating the global cluster coefficient. To assign a value to the 4-paths (see Fig. 2) the geometric mean is used. Instead of seeking closed 3-paths the redefined coefficient replaces them with closed 4-paths. On a global network level the clustering is measured. Hence

$$C_g = \frac{\text{total value of closed 4-paths}}{\text{total value of 4-paths}} \quad (13)$$

where the coefficient ranges from zero to one. Zero means there are no clusters at all and one stands for a highly clustered network. One can also interpret it as a measure of likelihood that actions are sharing same environmental components or vice versa.

2.2.0.6. Assortativity coefficient. In general, assortativity addresses the tendency of similar vertices (e.g., same ethnic group) to join each other (Newman 2010). By introducing external vertex properties the mixing pattern in the network can be described (Newman 2003). Due to this we classify the vertices with discrete categories. Instead of ethnic groups we label the vertices with the categories water, land, biology, socioeconomy and infrastructure. Newman (2003) defined the assortativity coefficient r for discrete characteristics as

$$r = \frac{\sum_{i=1} e_{ij} - \sum_{i=1} a_i b_i}{1 - \sum_{i=1} a_i b_i} \quad (14)$$

where e is the matrix which can be either the incidence matrix B or the adjacency matrix A whose elements are e_{ij} of the according matrix. e_{ij} quantifies the fraction of edges in a network that connect a vertex of category i to one of category j . a_i and b_i are the fraction of each category of an end of an edge that is attached to vertices of category i . The range of the assortativity coefficient is $-1 \leq r \leq 1$. Positive values are found when assortative mixing is present, which means vertices of same categories

are predominantly connected to each other and vice versa for negative coefficient, in which the vertices are mixed disassortatively. In terms of EIA an assortative mixing reflects that an intra-sectoral impact is prevalent, for example socioeconomic environmental components are mainly impacted by socioeconomic actions. By contrast, disassortative mixing describes an inter-sectoral impact which means that actions of one category (e.g. socioeconomic) affect categories such as land or biology (i.e. actions and environmental components do not belong to the same category).

2.3. Diagonalisation of the adjacency matrix

Diagonalisation of the matrix operator is a linear algebra's technique that allows to rewrite linear maps of finite vector spaces into a simpler and easier-to-handle form. We formulate the hypothesis that the decoupled impact of each action can be obtained by diagonalising the adjacency matrix. Thereby, one derives how much the actions need to be changed to sustain the network if a single action is altered. In order to diagonalise the action's adjacency matrix (see equation 2) we first need to determine the corresponding eigenvectors V

$$\mathbf{A}V = \lambda V \quad (15)$$

with λ as the corresponding eigenvalues. We derive then the diagonalised form of A by multiplying it with the eigenvectors and the inverse eigenvectors such that

$$A_D = V^{-1}AV \quad (16)$$

As the matrix is symmetric the diagonal contains the eigenvalues of A .

2.4. The graph Laplacian

The well-known diffusion process (e.g., from gaseous mixing) can be transferred to networks with the purpose to represent the propagation of information (Newman 2010). Thus, to incorporate this sort of process we introduce the *graph Laplacian* matrix L which is defined as the difference between the adjacency matrix A and their corresponding diagonal matrix D where the vertex degrees, k_i , are along its diagonal

$$L = D - A \quad (17)$$

More explicitly equation (17) can be expressed as

$$L_{ij} = \delta_{ij}k_i - A_{ij} \quad (18)$$

in it we recall the Kronecker delta δ_{ij} , which is 1 if $i = j$ and 0 otherwise. Hence, the elements of L_{ij} are

$$L_{ij} = \begin{cases} k_i & \text{if } i = j, \\ -A_{ij} & \text{if } i \neq j \text{ and there is an edge between } i \text{ and } j, \\ 0 & \text{otherwise.} \end{cases} \quad (19)$$

The *graph Laplacian* is a symmetric square matrix and describes the spreading of information applied at time $t = 0$ to the i -th vertex, $\psi_i(t)$, as a result of a diffusion process among vertexes driven by the vector of diffusion constants between two vertexes, C . This mechanism is driven by the systems of coupled linear ordinary differential equations (ODEs)

$$\frac{d\psi}{dt} = -C\mathbf{L}\psi. \quad (20)$$

The ODEs system (20) has a solution involving the exponential matrix, i.e.

$$\psi(t) = \psi_a e^{-tC\mathbf{L}}, \quad (21)$$

where t is time and ψ_a is a vector of constants to be determined by imposing the initial conditions $\psi_{ai} = \psi_i(0)$. An important physical property of the *graph Laplacian* is that the smallest value its eigenvalues can have is $\lambda_i = 0$, which means that the solutions in the form (20) or (23) are all decaying exponentials so that the solution tends to zero with the order of the smallest exponential as $t \rightarrow \infty$. Finally, it is worth to recall that the presence of a null eigenvalue implies that the *graph Laplacian* has no inverse, its determinant is zero and the matrix is therefore singular. However, if the eigenvalues are all nonzero, then the solution for $\psi(t)$ can also be written as a linear combination of the eigenvectors v_i of the Laplacian

$$\psi(t) = \sum_i a_i(t) v_i, \quad (22)$$

where $a_i(t)$ evolve according to the time dependent solution

$$a_i(t) = a_i(0) e^{-C\lambda_i t}, \quad (23)$$

where λ are the eigenvalues of the *graph Laplacian* matrix and $a_i(0)$ can be determined from the initial conditions $\psi_i(0)$. Given that environmental processes are coupled, information about the perturbation occurring to one such processes will therefore diffuse among the other processes. **At the first order of analysis, whether such an information will generate or not an unpredictable impact on other processes will however depend on their inherent nonlinearity and resilience to that specific perturbation. In other words, the degree of nonlinearity of the environmental process being considered and its non-normal properties (Camporeale and Ridolfi 2009), could cause substantial deviation from the linear picture as soon as nonlinear effects start prevailing. For example, as shown by Scheffer et al. (2001), ecosystem dynamics may experience catastrophic shifts when undergoing important perturbations; these effects would however not be predicted by the graph Laplacian analysis. Eventually, the *graph Laplacian* can therefore be considered as a screening tool to estimate how fast perturbations**

may propagate to other components under the assessed impact severity of actions on environmental components previously performed by the experts.

3. Examples of application

In the following, we use example data from three EIA case studies for which all the data has already been published. In some of the examples, the terminology used in the original literature is not necessarily correct to identify processes and may disagree with commonly adopted definitions. However, we deliberately maintained it here in order to keep the link with the original literature sources where the examples had been taken. Similarly, we did not perform any data screening here and assume the data to have genuinely been verified at the source. In general, in order to guarantee robust results from this methodology for practical applications, we recommend that the input data has to be first screened before applying the proposed approach.

3.1. Sugarcane plantation East Karun River, Iran

In this example the interaction matrix originates from Nahvi et al. (2017), in which they estimated the impacts of the drainage systems used for the development of sugarcane plantations at the East Karun River in Iran. The interaction matrix is illustrated in Table 1. ~~Like in the previous example~~ We can visually easily make out the actions and environmental components which have no affect or are not affected, respectively. However, soil is not positively impacted (Fig. 3b, 3a) while on the contrary only soil, the performance of the products and the economic income of the project and human societies hygiene in the project zone as environmental components are negatively impacted (Fig. 3d, 3a) and applying deficit irrigation, controlling the groundwater depth and discharge to evaporative lagoons as actions have a negative effect (Fig. 3e, 3a).

The main network statistics for this case study are given in Table 2. The network is strongly asymmetric (0.6) and has only a few negative interactions. Due to this the cluster and assortativity coefficient cannot be computed for the negative interactions. The mean distances ranging from 0.8 to 1.6 are quite small when it is connected with the number of vertices (Actions: 5, Environmental components: 20). A very high clustering is observed for the positive actions (0.99) which correlates with the strong asymmetry. In comparison for the positive environmental components only a moderate clustering coefficient (0.56) is obtained because the components sharing less actions together. Albeit, we detect a disassortative pattern in the networks.

To distinguish the actions and environmental components which are interacting on a high level from the ones on a low level regard Table 3. The reducing of the depth of the drainage system and reusing the drainage water (k_{23} : 58) is attributed by far the most dominant positive action . Comparatively small is the negative leverage of the applied deficit irrigation (k_{23} : 4). The effect on the general condition of the Shadegan Wetland environment (k_{29} : 21) benefits the most while human societies hygiene in the project zone (k_{218} : 3) and soil (k_{24} : 3) endure negative effects even though they have a small magnitude.

The degree distribution resulting from Table 3 is illustrated in Fig. 4. Degrees ranging from 24 to 27 exhibit the highest frequency for the actions with positive interactions. On the opposite the environmental components which are positively impacted have its highest frequencies in the lower range from 3 to 6. This is supported by its right-skewed shape which appears in a skewness of 1. Thus, more environmental

Table 1.: Interaction matrix for the sugarcane planation at the East Karun river, Iran (Nahvi et al. 2017)

		Actions				
		1	2	3	4	5
		Applying deficit irrigation	Controlling groundwater depth	Reducing the depth of the drainage system and reusing the drainage water	Cultivation of the salinity resistant plants	Discharge to evaporative lagoons
Environmental components	1 Flooding	0	0	0	0	3
	2 Temperature	0	0	0	0	1
	3 Physical airquality	0	0	2	2	0
	4 Soil	-2	-1	0	0	0
	5 Erosion	0	0	2	2	0
	6 Quantity of water	5	2	3	0	0
	7 Quality of water downstream	3	3	3	0	0
	8 Plant coverage	0	0	3	3	0
	9 Effect on the general condition of the Shadegan Wetland environment	3	4	5	4	5
	10 Wetland plant species environment	2	4	5	4	5
	11 Wetland animal species environment	1	3	4	0	4
	12 Wetland aquatic species environment	2	3	4	0	4
	13 Project zone plant species environment	0	0	5	2	3
	14 Performance of the products and the economic income of the project	-2	1	2	3	0
	15 Making jobs in the project zone	0	0	4	3	0
	16 Making jobs in wetland district	0	2	4	2	0
	17 Tourism performance in the wetland zone	0	3	3	0	0
	18 Human societies hygiene in the project zone	0	2	3	2	-3
	19 Human societies hygiene in the wetland zone	0	0	3	0	0
	20 Social justice	3	0	3	0	0

Figure 3.: The bipartite network (a) for the East Karun sugarcane plantation's interaction matrix separated into two networks containing the positive interactions (green, a) and the negative interactions (red, a), and the corresponding one-mode projections of the positive (green, b-c) and negative interactions (red, d-e). The width of an edge in (a) indicates the severity of an impact, whereas for (b-e) the edge width shows the shared impact by actions or environmental components, respectively. The vertex colour indicates to which category the actions and environmental components belong.

Table 2.: Main statistics of the bipartite network and the one-mode projections for the sugarcane planation at the East Karun river, Iran

	Two-mode				One-mode			
	positive interactions		negative interactions		positive interactions		negative interactions	
	Actions	Environmental components	Actions	Environmental components	Actions	Environmental components	Actions	Environmental components
Number of vertices	5	20	5	20	5	20	5	20
Number of edges	51	51	4	4	10	147	1	1
Network asymmetry			0.6				0	
Connectance		0.51		0.04	0.4	0.37	0.04	0.00
Mean distance	–	–	–	–	1.1	1.6	0.8	1
Cluster coefficient	0.99	0.56	–	–	–	–	–	–
Assortativity coefficient		-0.21		-0.6	-0.25	-0.07	–	-1

components are less affected by the actions.

Table 3.: Degree centrality and mean degree for the sugarcane planation at the East Karun river, Iran

Actions					Environmental components				
Two-mode		One-mode		One-mode		Two-mode			
j	positive in- teractions	negative in- teractions	positive in- teractions	negative in- teractions	negative in- teractions	positive in- teractions	negative in- teractions	positive in- teractions	i
1	19	4	48	2	0	18	0	3	1
2	27	1	73	1	0	6	0	1	2
3	58	0	121	0	0	50	0	4	3
4	27	0	60	0	2	0	3	0	4
5	25	3	70	0	0	50	0	4	5
$\overline{k2_j/k1_j}$	31.2	1.6	74.4	0.6	0	96	0	10	6
					0	93	0	9	7
					0	75	0	6	8
					0	200	0	21	9
					0	194	0	20	10
					0	121	0	12	11
					0	127	0	13	12
					0	116	0	10	13
					2	68	2	6	14
					0	91	0	7	15
					0	100	0	8	16
					0	75	0	6	17
					0	84	3	7	18
					0	48	0	3	19
					0	66	0	6	20
					0.2	83.9	0.4	7.8	$\overline{k1_i/k2_i}$

3.2. Kladovo wind farms, Serbia

For our second example the interaction matrix is derived from a case study on wind farms in Serbia (see Josimovic et al. (2014)). The matrix can be extracted from Table 4. In contrast to the two other case studies the matrix contains only positive values which made the separation of the network unnecessary. Fig. 5b and 5a reveal confirm that the environmental components water, microclimate, erosion and economy are not being influenced by any of the actions. In comparison every action bears an impact on the environment (Figure 5c, 5a) which can be more refined by looking at Table 5. From this we can identify the actions showing the strongest impact on the environment. These are the operation of construction equipment ($k2_7$: 18) and waste material treatment ($k2_8$: 18). And the one environmental component, which is the most impacted (i.e. most significant impact), is the landscape ($k2_{12}$: 15). The ones with the highest degrees in the two-mode showing also the highest degrees in the one-mode (see Table 5).

Shedding more light on Table 5 is provided by Fig. 6 which displays how the degrees in the bipartite network are distributed. It can be seen that every action has at least a moderate impact (i.e. the frequency of the first two bins of Fig. 6 is 0). The highest frequencies are found for the ranges from 6 to 9 and 15 to 18 and framing the histogram. On the other side the histogram of the environmental components proves the existence

Figure 4.: Degree distribution for the bipartite network of the East Karun case study with its statistical moments which are the arithmetic mean μ , the standard deviation σ and the skewness v . The distribution is shown for both the actions (a,b) and the environmental components (c,d) with positive (green) and negative (red) interactions.

of no or low impacts, but the highest frequencies for the degrees 9 to 12. Featured by a skewness of -0.4 emphasizes that higher impacts are slightly predominant.

The main network statistic in Table 6 reveal that the bipartite network is slightly asymmetric (0.28) and 56 % of all possible edges are realised. The connectance is lower in the one-modes of the actions (0.44) and the environmental components (0.25). Likewise, mean distances in the one-mode are found to be very low (Actions: 1.2, Environmental components: 1.6) as the number of vertices for the actions and for environmental components are 9 and 16, respectively. Unlike the clustering which is exceptional high with coefficients of 1 and 0.96 underpins the network complexity. We also encounter a disassortative mixing pattern verified by the negative assortativity coefficients.

3.3. Tallahalla dam, USA

The last example deals with the Tallahalla Dam project at the Mississippi in the USA (see Jain and Singh (2003)). Here we are making use of the interaction matrix obtained by the EIA, which was carried out in the run-up of the project. The interaction matrix is shown in Table 7. The nested interactions among actions and environmental components makes it difficult to understand for instance both the global picture and the interdependencies between actions and affected environmental components. Hence, the interpretation as a network comes into help here. Consider Fig. 7 in which the bipartite network and the corresponding one-mode projections resulting from Table 7 are plotted. Inferring from Figure 7, one immediately detect that that the environmental

Table 4.: Interaction matrix for the wind farms at Kladovo, Serbia (Josimovic et al. 2014)

		Actions								
		1	2	3	4	5	6	7	8	9
		Placement of wind turbines	Foundation of columns	The use of building materials	Substation construction	Transmission line construction	Construction of internal roads	Operation of construction equipment	Waste material treatment	Project exploitation
Environmental components	1 Water	0	0	0	0	0	0	0	0	0
	2 Microclimate	0	0	0	0	0	0	0	0	0
	3 Land	1	2	1	1	1	1	2	2	1
	4 Erosion	0	0	0	0	0	0	0	0	0
	5 Air	0	0	0	1	0	2	3	1	0
	6 Noise	1	1	1	2	1	2	3	0	2
	7 Diversity of flora	0	1	0	0	1	0	1	1	0
	8 Diversity of fauna	2	1	1	1	1	0	2	2	2
	9 Ornithofauna	2	1	1	1	1	0	2	2	2
	10 Chiropteran fauna	2	1	1	1	1	0	2	2	2
	11 Barriers/corridors	2	1	1	1	1	0	1	1	2
	12 Landscape	2	2	1	2	1	1	1	3	2
	13 Land use	1	2	1	1	1	1	1	2	1
	14 Economy	0	0	0	0	0	0	0	0	0
	15 Cultural heritage	0	2	0	0	0	0	0	0	0
	16 Accidents	2	0	0	1	0	0	0	2	2

Figure 5.: The bipartite network (a) for the Kladovo wind farms' interaction matrix and the corresponding one-mode projections (b-c). The width of an edge in (a) indicates the severity of an impact, whereas for (b-c) the edge width shows the shared impact by actions or environmental components, respectively. The vertex colour indicates to which category the actions and environmental components belong.

Table 5.: Degree centrality and mean degree for the wind farms at Kladovo, Serbia

Actions			Environmental components		
j	Two-mode	One-mode	One-mode	Two-mode	i
1	15	101	0	0	1
2	14	86	0	0	2
3	8	59	98	12	3
4	12	80	0	0	4
5	9	62	53	7	5
6	7	44	101	13	6
7	18	114	35	4	7
8	18	117	101	12	8
9	16	108	101	12	9
$k2_j/k1_j$	13	85.7	101	12	10
			83	10	11
			123	15	12
			89	11	13
			0	0	14
			18	2	15
			59	7	16
			60.1	7.3	$k1_i/k2_i$

Table 6.: Main statistics of the bipartite network and the one-mode projections for the wind farms at Kladovo, Serbia

	Two-mode		One-mode	
	Actions	Environmental components	Actions	Environmental components
Number of vertices	9	16	9	16
Number of edges	80	80	36	64
Network asymmetry		0.28		0
Connectance		0.56	0.44	0.25
Mean distance	–	–	1.2	1.6
Cluster coefficient	1	0.96	–	–
Assortativity coefficient		-0.56	–	-0.12

Figure 6.: Degree distribution for the bipartite network of the Kladovo case study with its statistical moments which are the arithmetic mean μ , the standard deviation σ and the skewness v . The distribution is shown for both the actions (a) and the environmental components (b).

Table 7.: Interaction matrix for the Tallahala dam at the Mississippi, USA (Jain and Singh 2003)

		Actions									
		1	2	3	4	5	6	7	8	9	10
		Flood control	Water supply	Water quality	Dam	Dyke	Conduit	Lake	Shoreline	Clearing vegetation	Road construction
Environmental components	1 Flooding	2	0	1	2	1	0	2	0	0	1
	2 Water supply	0	2	1	2	0	2	2	0	0	0
	3 Potable water	0	1	2	2	0	0	0	0	0	0
	4 Pollution	1	0	2	2	0	0	2	0	0	0
	5 Sedimentation	2	0	1	-1	1	0	-1	0	0	0
	6 Erosion	2	0	0	1	1	0	1	0	-2	-1
	7 Hydrography	1	0	0	1	-1	0	1	0	-1	0
	8 Microclimate	-1	0	0	1	0	0	-1	0	-1	0
	9 Land upstream	0	0	0	-2	-1	-1	-2	0	-2	0
	10 Land downstream	2	1	1	1	0	0	1	0	0	-1
	11 Forest upstream	-2	0	0	-2	-1	-1	-2	-1	-2	0
	12 Forest downstream	1	0	1	1	0	0	1	0	0	-1
	13 Fishery	2	0	2	2	0	0	2	0	0	0
	14 Wildlife	1	0	0	-2	-1	0	-2	0	-2	-2
	15 Endangered bird species	0	0	0	-2	0	0	-2	-1	-2	-1
	16 Ecosystem	1	0	1	-2	-1	0	-2	0	-1	-1
	17 Health insect vector	-2	1	1	-2	0	0	-2	0	0	0
	18 Recreation	1	0	1	1	0	0	1	2	-1	2
	19 Economic activities	2	1	2	1	0	0	1	0	-1	2
	20 Population displacement	0	0	0	-1	0	0	-1	0	0	0
	21 Transports	1	0	0	1	0	0	1	0	1	2

components land upstream, forest upstream, endangered bird species and population displacement do not receive any positive impact (Figure 7b, 7a). On the other hand, the environmental components flooding, water supply, potable water, fishery and transports undergo evidently no harm (Fig. 7d, 7a). Likewise, the actions water supply and water quality have no negative effect on the environment (Figure 7e, 7a).

In Table 8 the main statistics for the bipartite network and the one-mode projections of the Tallahala dam are summarised. The first four rows are describing the general network characteristics while the last three rows are elaborating the network structure. The connectance shows that the bipartite network with the positive interactions got more edges than the one with the negatives. ~~To determine whether the positive impacts are outweighing the negative impacts, we~~ **It is also instructive to** consult Table 9 in which the weighted degrees and mean degrees are stored. The mean degrees in the bipartite network of the positive interactions (Actions: 8.9, Environmental components: 4.2) are higher than the mean degrees of the negative interactions (Actions: 6.5, Environmental components: 3.1), ~~it reveals that the positive impacts are greater~~ **thus suggesting the prevalence of a positive impact. However, we stress here that a definitive statement in this direction can only be assumed in relative but in absolute terms. This is consequence of the fact that impact evaluation performed by experts on each environmental component does not allow to compare the significance of a given impact with respect to other environmental components.** The mean distances found in the one-mode projections vary from 1.2 to 2.6. These distances take quite small values compared to the number of vertices in the networks (Actions: 10, Environmental components: 21). The phenomenon of small distances in networks is also known as the small-world effect (Newman 2010). Contrary to this the cluster coefficients in the two-mode range from 0.57 to 0.82 suggesting a high network complexity. The lower clustering for the environmental components with negative impact means that they have less actions in common than for the positive impacts. Negative values without exception for the assortativity coefficient for both the bipartite network and the one-mode projection unveil the disassortative mixing pattern. This means that the vertices with unlike categories (e.g. water and biology) tend to connect with each other as also expected for other reasons, for example, biological in the mentioned case.

From Table 9 we can recognize that flood control (**k_{21} : 19**) has the most positive

Figure 7.: The bipartite network (a) for the Tallahala dam's interaction matrix separated into two networks containing the positive interactions (green, a) and the negative interactions (red, a), and the corresponding one-mode projections of the positive (green, b-c) and negative interactions (red, d-e). The width of an edge in (a) indicates the severity of an impact, whereas for (b-e) the edge width shows the shared impact by actions or environmental components, respectively. The vertex colour indicates to which category the actions and environmental components belong.

Table 8.: Main statistics of the bipartite network and the one-mode projections for the Tallahala dam at the Mississippi, USA

	Two-mode				One-mode			
	positive interactions		negative interactions		positive interactions		negative interactions	
	Actions	Environmental components	Actions	Environmental components	Actions	Environmental components	Actions	Environmental components
Number of vertices	10	21	10	21	10	21	10	21
Number of edges	64	64	45	45	33	126	26	75
Network asymmetry			0.35				0	
Connectance		0.30		0.21	0.33	0.29	0.26	0.17
Mean distance	—	—	—	—	2.6	1.2	1.2	1.9
Cluster coefficient	0.82	0.80	0.84	0.57	—	—	—	—
Assortativity coefficient		-0.15		-0.15	-0.15	-0.04	-0.15	-0.10

impact whereas the actions of clearing vegetation (k_{29} : 15) and lake (k_{27} : 15) have the most negative impact in the bipartite network. Flood control (k_{11} : 62) and lake (k_{19} : 52) exhibit also the highest degrees in the one-mode. Among the environmental components forest upstream (k_{11} : 11) is the most compromised and flooding (k_{21} : 9), water supply (k_{22} : 9) and economic activities (k_{219} : 9) are the most positive affected ones in the bipartite network. The highest degrees in the one mode do not correspond to the highest degrees found in the two-mode. These are fishery (k_{213} : 90) for the positive interactions and wildlife (k_{214} : 62) for the negative interactions.

The results from Table 9 can be more refined by plotting its histograms which are shown in Fig. 8. All histograms have in common that the highest frequencies occur for the first bin which ranges from 0 to 3 and means that no or low impacts are dominating. But not as much as in Fig. 8b in which the degrees from 12 to 15 and Fig. 8c from 3 to 9 bear almost the same frequencies.

Finally, for this case we show the results of the Graph Laplacian (Figure 9). These plots show the response of the environmental components when the actions of clearing

Table 9.: Degree centrality and mean degree for the Tallahala dam at the Mississippi, USA

Actions				Environmental components					
Two-mode		One-mode		One-mode		Two-mode			
j	positive in- teractions	negative in- teractions	positive in- teractions	negative in- teractions	negative in- teractions	positive in- teractions	negative in- teractions	positive in- teractions	i
1	19	5	62	18	0	84	0	9	1
2	6	0	20	0	0	63	0	9	2
3	16	0	51	0	0	50	0	5	3
4	18	14	60	50	0	78	0	7	4
5	3	5	10	19	15	37	2	4	5
6	2	2	8	10	23	48	3	5	6
7	15	15	56	52	13	34	2	3	7
8	2	2	10	10	19	12	3	1	8
9	1	15	4	45	53	0	8	0	9
10	7	7	33	17	5	61	1	6	10
$\overline{k2_j/k1_j}$	8.9	6.5	31.4	22.1	58	0	11	0	11
					5	45	1	4	12
					0	90	0	8	13
					62	12	9	1	14
					54	0	8	0	15
					48	23	7	2	16
					34	15	6	2	17
					9	51	1	8	18
					9	78	1	9	19
					15	0	2	0	20
					0	40	0	6	21
					20.1	39.1	3.1	4.2	$\overline{k1_i/k2_i}$

Figure 8.: Degree distribution for the bipartite network of the Tallahala case study with its statistical moments which are the arithmetic mean μ , the standard deviation σ and the skewness ν . The distribution is shown for both the actions (a,b) and the environmental components (c,d) with positive (green) and negative (red) interactions.

Figure 9.: Graph Laplacian of the Tallahala case study. (a) Initial perturbation as input of clearing of vegetation in the upstream forest. (b) Initial perturbation as input of sedimentation due to dam construction and lake formation.

vegetation and dam construction impact first on the forest upstream and the sedimentation in the lake, respectively. Values are normalized to have unitary impacts on forest upstream and sedimentation, whereas the time scales are normalized to a reference time for such impacts to take place. In the limits of the linear picture provided by the Graph Laplacian one appreciates the way the perturbations above said propagates to the other environmental components and the related timescales. For example, the input of clearing vegetation (Figure 9a) on the forest upstream decays quickly meaning that this effects spreads across other environmental components with different dynamics. Thus, land upstream immediately peaks and then decays while affecting with a delayed effect population displacement (e.g., less attractive areas for recreational activities, etc.) and the forest downstream (e.g., recruitment of young species due to seed dispersal for instance). Figure 9b shows the effect of dam construction as an input of changing sediment propagation across the alluvium. Trapping of sediments by the dam, for instance, occurs gradually and results in a sorting mechanism downstream, which affects the land downstream, the hydrography as a changing morphodynamic processes and more slowly this will have an impact on the forest downstream (e.g., sediment sorting propagates to the floodplain during sporadic inundations and in turn affects vegetation growth in the long term).

4. Discussion

Comparing our results from the three examples of application to the results derived by traditional analysis of EIA (Jain and Singh 2003; Josimovic et al. 2014; Nahvi et al. 2017), the results are generally in agreement. However, the comparison reveals the added value through our approach. Although the network visualisation accounts appropriately for the complex interactions, ~~most~~ beneficial or ~~most~~ harmful actions can be easier identified. Moreover, in terms of inferring potential mitigation measures our approach ~~outperforms~~ **complements** traditional analysis approaches. This could be shown for three examples of application. For the case of the sugarcane plantation East Karun River (see section 3.1.), ~~actions have obviously less negative impact. Most~~ **beneficial actions can be easily distinguished and knowledge about which actions are decoupled enhances substantially the planning of mitigation measures.** Clearly, the discharge to evaporative lagoons can be treated independently whereas applying deficit irrigation and controlling the groundwater depth are coupled (see Figure 7). Concern-

ing mitigation measures, these two actions have to be considered simultaneously. The application for Kladovo example (see section 3.2.) exposes that the actions are strongly coupled (see Figure 3). Environmental components categorised as biology and land are impacted by same actions. Thus, potential mitigation measures have to consider the complex impact pattern and mitigation will mainly affect biologic and land environmental components. The results derived for the Tallahala dam example (see section 3.3.) help to constrain the mitigation measures. Major mitigation can be achieved by focussing on measures which are addressing flood control, water quality, dam and lake (see Figure 5). The low disassortative mixing underlines that inter-sectoral solutions may be more promising (see Table 8).

Our approach appends to already existing network theory approaches (e.g. Martínez et al. (2018)). In contrast to Martínez et al. (2018) we provide a sound theoretical framework and impact patterns can immediately be detected. We showed how the network theory approach may help interpreting the meaning of the Interaction Matrix via one-mode and two-mode projections and related metrics. Nevertheless, the loss of information is a key issue one needs to bear in mind when projecting the network. More specifically, this means that the projection does not preserve the information of which environmental components are shared by an action with other actions or which actions are shared by an environmental component with other environmental components. Conversely, this also means that one cannot a priori reconstruct the bipartite network when starting from the projection only. However, the one-mode projection is helpful to deduce what is the shared impact among the actions or among the components. The strength of the projections is therefore rather to make a statement on the interconnections among the actions or among the environmental components. This helps figuring out what is the impact one action is sharing with others or, from the perspective of the environmental components, what impact has one component in common with others. Apparently, vertices with the highest degrees have not necessarily the highest degrees in the one-mode. As shown in Fig. 7b-e, 3b-c and 5b-e these interconnections can be quite complex. Therefore, the diagonalization of the action's adjacency matrix intends to facilitate the comprehension of the interconnections.

The three examples have shown that the proposed approach has high potential in helping the interpretation of the Interaction Matrix when the network exhibits a certain complexity. We used three examples of different complexity for this purpose. For example, the negative interactions in the sugarcane plantation in East Karun (see Fig. 3a, Fig. 3d-e, Fig. 4b and Fig. 4d) encompass only a single edge and its network structure is already very simple. As a consequence, the higher the complexity of the Interaction Matrix, the more helpful are its representation and study through the network approach.

From the main network statistics (see Table 2, 6, and 9) we could deduce some common features for the three case studies. These are high clustering, disassortative mixing, short distances and a general asymmetric structure. Hence, the applied measures and metrics emphasise the complex character of the networks despite the relatively small size compared to other papers dealing with bipartite networks (Dorrmann et al. 2009; Guillaume and Latapy 2004; Newman 2001a,b; Amaral et al. 2000; Watts and Strogatz 1998).

The results we found for the assortativity coefficients are only valid for the categories we used. These results can differ if one classifies the actions and environmental components differently. Also the example of the wind farms in Kladovo has shown that a clear classification into several categories can be difficult. This leads to that all vertices for the actions are labeled with the same category (see Fig. 5). In this case the

assortativity coefficient for the bipartite network will always be negative and for the one-mode projection of the actions the assortativity coefficient will return no result.

As far as the use of the Graph Laplacian is concerned, one must bear in mind that the linear picture does not consider nonlinear effects as thresholds, amplifications and smoothing, feedbacks, etc. that may arise while the effects propagate across the environmental components. This may preclude the interpretation of the effects on the long term. The linear picture shows indeed that at the beginning diffusion of information propagates with the eigenvalues proper of each environmental component. In the long term, however, all perturbations will decay to zero with the time scale imposed by the lowest eigenvalue, which may not have physical meaning as nonlinear effects may take place. Thus, the Graph Laplacian is fairly accurate to determine the initial cascade of effect propagation, which can be useful to understand whether the Interaction Matrix had been built in a meaningful way or whether it must be reconsidered for minor adjustments.

5. Conclusions

Using network theory, we showed that the interpretation of the interaction matrix as a bipartite network hinders further interesting information if related projection modes are calculated. Beyond typical statistical measures, **projection modes give access to the calculation of the graph Laplacian, which is one of the novelty analyses introduced by this work.** In general, the three real case studies proved the general applicability of our approach **for the original data quality and reliability available online.** Combining the network in its visual form with the measures and metrics allows to unravel its complex character **and thus complements the early work performed by Perdicoulis and Glasson (2006).** With the proposed approach **the most important the relative role of actions and environmental components with respect to the degree of positive and negative impact attributed by experts** can be detected very quickly and at the same time the distinction between the ones which are **less or not involved at all in the impact dynamics is facilitated,** respectively. ~~Together with the Graph Laplacian information, this is more illuminating than just learning from the Interaction Matrix itself. Together with the information provided by the graph Laplacian, the other measures of the network approach increase the level of information contained in the Interaction Matrix itself. The presented methodology adds to recently proposed methodologies that have already implemented complex network theory.~~ The identification of impacts and evaluation of its significance may enhance the planning and enforcing of mitigation measures. Moreover, ~~we overcome subjectivity of traditional EIA analysis. We think~~ This quantitative analysis can therefore provide essential information to the decision-making process of corresponding project for which the EIA was carried out.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Both authors have contributed equally to all aspects of this work.

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